**Quantified, Localized Health Benefits of Accelerated Carbon Dioxide Emissions Reductions**

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**Supplemental Discussion**

*1. Utilizing constituent moments to produce high-resolution concentrations*

Second-order moments (first and second derivatives) have long been used for advection of both physical "parameters" such as heat and transported constituents (sometimes referred to as 'tracers') in our model [27]. We have now implemented a mechanism to take advantage of those moments to create constituent fields at higher resolution than the model's basic grid box resolution. We incorporate high-resolution emissions information, using that to alter not only the grid box tracer mass but also the horizontal tracer moments (x, y, xx, yy, and xy). Those moments are then used in the dynamics, as they have been for decades, and diagnostics are expanded to output those five moments along with the standard output of constituent mass. Those six quantities are then used to redistribute constituents within the large model grid box while preserving the total, arriving at a higher-resolution distribution of surface pollutants. For sulfate, we incorporate the $SO_2$ moments within the chemical production of $SO_4$ as this pathway is fairly straightforward. Other chemistry involves multiple pathways and so does not incorporate sub-grid scale information.

To illustrate the effect of this new technique, we show surface $PM_{2.5}$ concentrations over East Asia, a region with very high $PM_{2.5}$ levels (Figure S1). There is a clear redistribution of pollution with the incorporation of constituent moments. This is particularly obvious near coasts where emissions gradients can be extremely large. For example, the native 2 x 2.5 degree simulation shows elevated $PM_{2.5}$ throughout a large grid box at the northwest corner of South Korea, more than half of which extends out over the ocean.

Incorporating moments within emissions, sulfur chemistry and post-processing redistributes the concentration to be far higher over the land area within this box, which includes the cities of Seoul and Incheon. A similar redistribution is visible at the Yangtze River delta where Shanghai is located. Moving inland, urban centers can be discerned more readily with the use of moments, for example Xian in the northwest of China. The maximum values obtained in polluted areas are increased as well, such as in Hong Kong/Guangzhou, Shanghai and Tokyo.

Comparison with observations shows improvement, in particular reducing the overall low bias seen in comparisons with urban measurements. For example, for the 61 urban centers among the top 103 in Table 1 (those with >100,000 premature deaths prevented, hence the most important for our results) for which directly measured $PM_{2.5}$ observations (i.e. rather inferred from $PM_{10}$ measurements) were available in the 2016 World Health Organization's database of ambient air pollution (data spanning 2009-2014) [34], the typical low bias of a coarse grid global model is greatly reduced with the use of moments (Figure S2). Specifically, in those 61 cities the mean bias in the base case is -9.3 µg m$^{-3}$ (17%) whereas in the case with moments the bias is reduced to -3.8 µg m$^{-3}$ (7%). Clearly the model remains imperfect (Figure S2), but at the same time it is substantially improved for the purpose of metropolitan area air quality modeling. We note that the model did exhibit substantial low biases in surface $PM_{2.5}$ over South Asia (India, Pakistan and especially Bangladesh). As the model exhibits its most pronounced precipitation biases by far of those seen over any land areas in this region [24], we expect that the bias is largely attributable to the model's failure to accurately reproduce the Asian Monsoon. Since this would affect large areas (not only urban centers), a bias adjustment was applied to all values in those three countries. Impacts of this bias adjustment are within the uncertainty in the exposure-response function, however.

Across the 61 cities evaluated here, the mean absolute bias in the model was 30% relative to observations (after bias adjustment). It would certainly be valuable to explore the results from regional modeling that might better capture urban-area $PM_{2.5}$, in particular for cities in South Asia. However, as the uncertainty of the cumulative deaths

based on the exposure-response function is 44%, values in most areas would likely remain within the ranges given here. Note also that a recent analysis using similar exposure-response relationships and a satellite-based analysis of surface PM$_{2.5}$ found that the global 2010 impact was ~3.9 million premature deaths, a value consistent with our 3.6±0.9 million from PM$_{2.5}$ (including thresholds, as in the other study) [33].



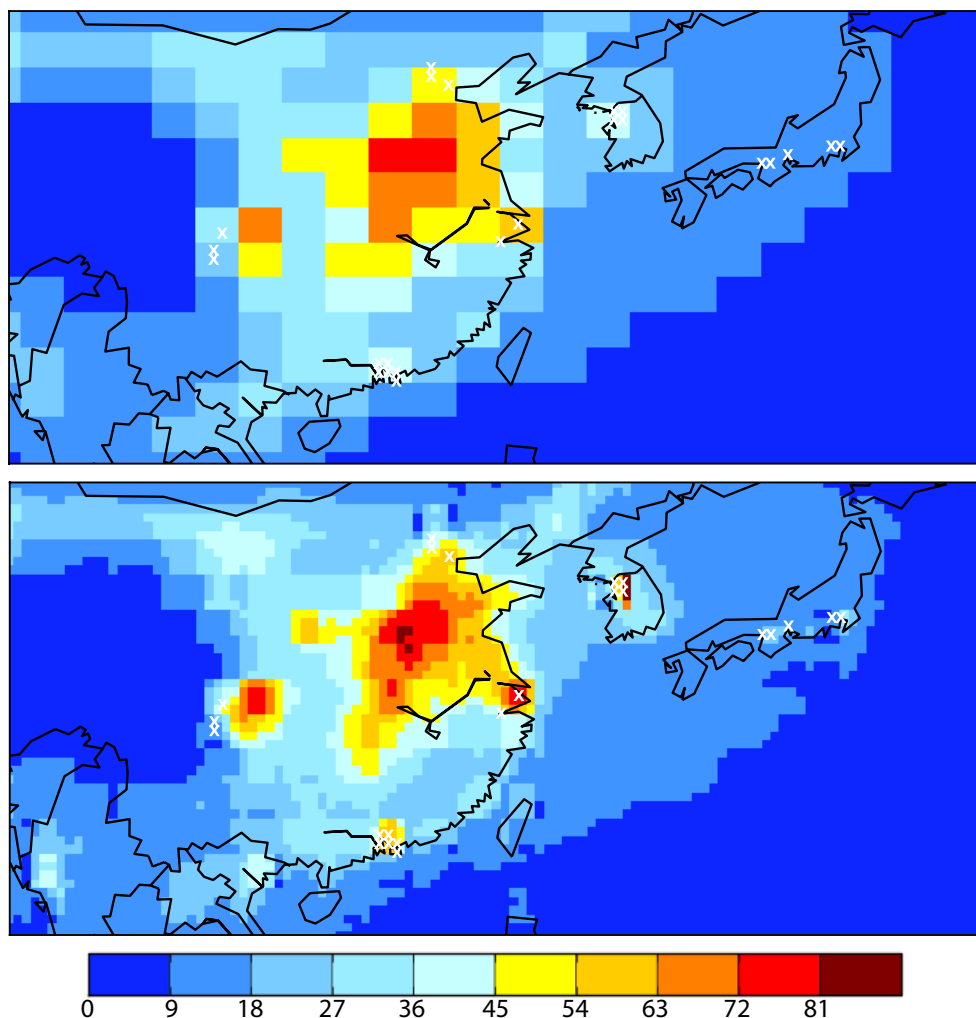Figure S1. Native 2 x 2.5 degree horizontal resolution simulation of present-day (2010) surface PM$_{2.5}$ ($\mu$g m$^{-3}$) over East Asia, and the 0.5 x 0.5 degree results incorporating first- and second-order horizontal moments in emissions, sulfur chemistry, and post-simulation concentration reconstructions. 0.5 x 0.5 degree boxes with more than 5 million inhabitants are marked with a white X.
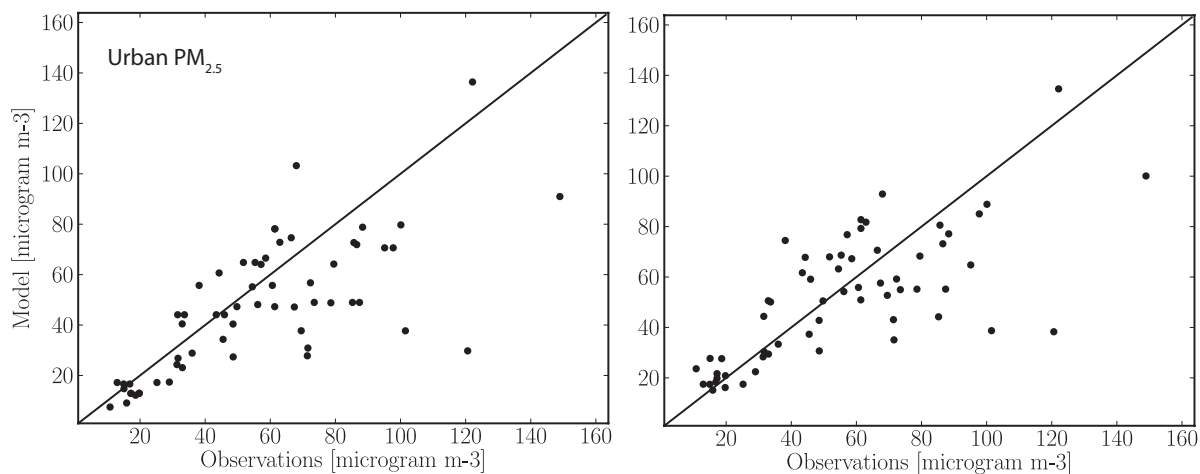
Figure S2. Urban annual average PM2.5 observations versus model results for the grid box containing the observed location using the model's native 2 x 2.5 degree resolution (left column) and the 0.5 x 0.5 degree results incorporating first- and second-order horizontal moments in emissions, sulfur chemistry, and post-simulation concentration reconstructions (right column). Data is shown for the 61 of 103 cities with value >100,000 in Table 1/S1 for which data is reported from direct $PM_{2.5}$ observations.

*2. Calculation of monetized near-term, long-term, local and remote impacts*

In order to better understand the relative importance to society of environmental damages attributable to climate and air quality over various spatial and temporal scales, we evaluated the social costs of all atmospheric emissions from various sources based on prior work that developed the Social Cost of Atmospheric Release [11], now separating these into near-term, long-term, remote and national damages. Here we define near-term as the fraction of damages that occur during the first 10 years, whereas long term is everything occurring after 10 years. Local damages are defined as the national portions of surface land area for a large nation such as the US or China or a block of smaller nations such as the EU (~6% of the world's surface area) for impacts related to climate and agriculture and for methane's effect on health via ozone. Remote is defined as the remainder, except for composition-health impacts for which 90% of PM-related health impacts are considered local and the rest remote (based on [35]).

We find that the bulk of damages attributable to current emissions from US coal-fired power plants are near-term and local: 58% with a 3% economic discount rate (range of 51 to 72% with 1.4% and 5% discounting, respectively). With their greater emissions of traditional air pollutants, the values are higher for Chinese coal-fired power plants: 64, 69 and 78% for 1.4, 3 and 5% discount rates, respectively, a pattern likely repeated in most developing countries. For US surface transportation, which is more highly co-located with population than power plants, the share of damages that are local and near-term is 68% with a 3% discount rate (range 62-77%). Though valuation of climate-related benefits would greatly increase over time, this suggests that near-term societal benefits of many sectoral transformations within a rapid low carbon transition would likely be dominated by human health gains that are themselves overwhelmingly attributable to air quality (more than 99% of the near-term, national effects stem from air quality-health impacts). These results motivate this study to probe deeper into the near-term, national effects, with a focus on air quality, in examination of the impacts of the various scenarios, and in particular to highlight the effects on individual

metropolitan areas as research indicates that highlighting risks for specific localities more effectively communicates the damaging effects of climate change [36, 37].

Note that some other sectors show a much smaller share of benefits occurring locally and in the near-term. For example, many of the damages associated with use of natural gas come from fugitive methane emissions and so are near-term (~30%), but only a small portion are localized to the nation where emissions take place (~5% of total damages for the US).

**Coal-fired Electricity: US    Transportation: US**

**Coal-fired Electricity: China**

■ long-term & national
■ long-term & geographically remote
■ near-term & geographically remote
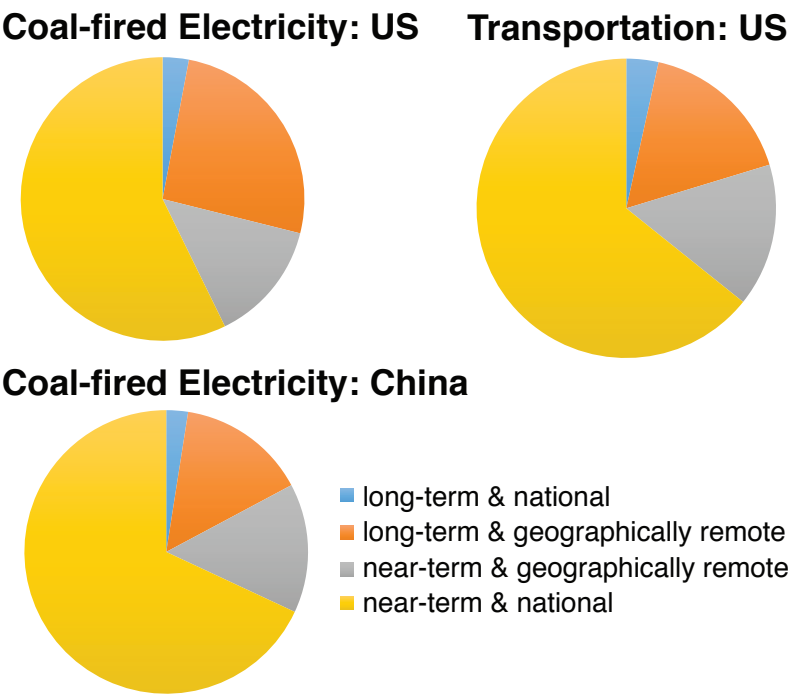■ near-term & national

Figure S3. Share of total valuation of environmental impacts of 2010 emissions from coal-fired power plants in the US and China and in US gasoline-powered surface transportation.

*3. Ozone Evaluation and Bias Correction*


We compared model output with observed mean annual daily 8-hr maximum concentrations for 83 urban areas in the US and China using hourly data from the U.S. EPA's Air Quality System and from the Beijing Municipal Environmental/China National Environmental Monitoring Centers (http://beijingair.sinaapp.com). Unlike $PM_{2.5}$, for which the systematic bias is weakly negative (Figure S2), the GISS-E2 model tends to overpredict urban surface ozone levels, as do most models. Surprisingly, biases in the US and China are nearly identical, suggesting that this evaluation is likely broadly applicable. Reducing mean annual daily 8-hr maximum ozone concentrations by 25% eliminates the bias, and so as a conservative approach we reduced ozone worldwide by this factor (adjusting based on the ppb bias would lead to smaller changes in more heavily polluted areas, while no adjustment would lead to overestimated impacts).

The bias adjustment of ozone reduces the integrated 21st century impacts by 19 and 39% when thresholds are not and are used, respectively (see SI.4 for additional discussion of thresholds). Thus the influence of the ozone bias correction is comparable in magnitude to the 30% uncertainty in ozone impacts stemming from the exposure-response relationship (the relative risk values) and 26% stemming from the choice of whether or not to use a low exposure threshold (leading to a combined methodological uncertainty of 39%). Hence improved ozone modeling could lead to improvements in health impact estimates (though given the dominance of PM-related impacts, ozone bias corrections remain a relatively minor source of total uncertainty). We point out that the use of a threshold makes the results much more sensitive to model biases, as small changes can lead to large impacts as values cross the threshold, so that uncertainties are larger when thresholds are used (as is the case for PM impacts; see SI.4). Our bias for all available areas is 6% less, indicating that urban areas are slightly more biased than rural, presumably due to titration at high levels of nitrogen oxides that is not fully resolved by the model (and hence our bias adjustment based on urban data will lead to underestimated non-urban impacts, but these should similarly not be markedly so).

*4. Alternative Calculations of Ozone-Health Impacts and Use of Low Exposure Thresholds*

*for Ozone and PM$_{2.5}$*


For comparison with prior studies, we not only calculated ozone-related health impacts using the most recent relative risk functions, but also including two older relative risk functions. The first comes from an American Cancer Society US study associating long-term ozone exposure with premature death from respiratory disease [38] (an earlier, smaller sample from the same study used in the newer analyses [29]). This RR has a value of 1.04 per 10 ppb increase in the maximum 6-month average of the 1-hr daily ozone maximum [18]. The second relative risk function is based on short-term exposure [39], and assigns most impacts to increased cardiovascular disease using a RR of 1.11 for a 10 ppb increase in 24-hr ozone concentrations based on a meta-analysis [40]. We reported the mean of these two methods with uncertainties representing the range between these two results as our 'legacy' calculation when comparing with prior analyses that relied upon similar relative risk functions in the Methods section. As these older methods included much weaker exposure-response functions, unsurprisingly they yielded markedly smaller impacts of the accelerated emissions cuts even though we did not include exposure thresholds (but did incorporate ozone bias-adjustment). Cumulative avoided premature deaths due to ozone were 17±4 million using legacy methods, less than half the 36±10 million found using the updated exposure-response functions for respiratory causes only including an exposure threshold or 41±9 million without a threshold.

We note that the updated exposure-response functions were obtained from an extended analysis of the same underlying dataset used in the prior 'legacy' exposure-response functions [38], and this larger dataset (covering more subjects over longer times) was analyzed by many of the same authors as the earlier work. Although it has not yet been widely used in health studies, it therefore seems sensible that it should supersede the prior methods. One recent study does utilize these newer exposure-response functions, and finds an even larger increase in the premature deaths associated with ozone [41],

though they analyze respiratory-related deaths only. As reported in the Methods section, that study utilized a different model's ozone and did not discuss comparison with observations or bias adjustment. Hence our smaller values for respiratory impacts appear related to our use of bias-adjusted modeled ozone. Ozone-related premature deaths are attributable to respiratory diseases and circulatory (cardiovascular diseases plus diabetes) in the newer analysis, and in our study the cumulative impacts of these are 36±10 and 24±15 million, respectively (including the exposure threshold). Hence respiratory impacts are likely the largest, and uncertainties associated with those are substantially smaller than those for circulatory diseases. We note that the circulatory responses were robust in the large recent analysis [29], and recent work has shown plausible biological mechanisms by which ozone can contribute to cardiovascular disease [42], hence we include these outcomes even though they have not yet been widely accepted (e.g. by the WHO).

The results are sensitive to assumptions about impacts at low ozone levels, especially below the lowest level at which exposures took place in the epidemiological studies which are commonly used as lower thresholds. As shown in the main text (Figure 2), under the accelerated reductions scenario ozone values in most of the world drop below the 26.7 ppb threshold by 2080, resulting in a decrease to near-zero ozone-related deaths in the last decades of the century when an exposure threshold is used.

Most literature follows the conservative judgment of the health research community to only include results at exposures that have been observed, meaning using a low exposure threshold. It is improbable, however, that the effects of air pollution abruptly vanish below measured levels, and indeed biological models do not make a convincing case for 'safe' exposure levels. Hence incorporating the measured exposure-response curves all the way to zero might make more sense despite the lack of observations at very low exposures. In support of this approach, a recent study [43] with a very large sample size (>60 million persons) has demonstrated that at the lower end of observed exposures, all cause premature death associated with an incremental ozone increase was only marginally weaker and statistically indistinguishable from that at higher exposures,

(as the analysis in [29] found statistically indistinguishable results with and without a threshold). In that same study [43], for PM$_{2.5}$ all-cause mortalities the relative risk for an incremental change in exposure actually increased substantially at lower exposures, undermining the rationale for including a so-called 'counterfactual' low exposure threshold.

For this reason we also included impact calculations for PM$_{2.5}$ and ozone that did not include an exposure threshold. As discussed in the main text, the use of a threshold leads to much lower total values but has much less effect on the impact of the accelerated emissions reductions. When thresholds are used for PM$_{2.5}$ exposure, the impacts of the accelerated emissions reductions begin to shrink rapidly towards the late 21$^{st}$ century, however, due to many areas falling below the threshold whereas in the calculations without a threshold the impacts vary smoothly through time and remain fairly constant from 2050 through 2100 (Figure 2). We point out also that the relative uncertainty associated with the PM$_{2.5}$ impacts is substantially less in the case without an exposure threshold. This is because the 1000 variants of the exposure-response function produce a wider range of outcomes in the case with the threshold as the simulated values fall below the threshold in some variants but not in others, creating large divergences. Such behavior does not occur when thresholds are not used. Worldwide cumulative deaths attributable to PM$_{2.5}$ are well within the uncertainty range of the threshold-based values when no threshold is used, however.

For ozone, the impacts of the accelerated emissions reductions similarly begin to shrink rapidly towards the late 21$^{st}$ century when a threshold is used due to many areas falling below that value (Figure 2). Relative difference between worldwide cumulative global deaths averted by the accelerated emissions reductions are greater for ozone than PM$_{2.5}$, but the cases with and without a threshold again have overlapping uncertainty ranges. As discussed in SI.3, uncertainties associated with model biases are larger for ozone-related deaths when using a threshold than in the no-threshold case. Based on the epidemiological evidence against 'safe' low-level exposures along with the absence of artificial changes in impacts when projected values cross thresholds (see also Figure S5)

and the reduced uncertainties and sensitivities to model biases in the absence of thresholds, we favor the results without exposure thresholds but present both for consistency with the general practice of incorporating exposure thresholds. We note that when no thresholds are used, it may be useful to compare impacts with those attributable to preindustrial air pollutant concentrations rather than zero to reveal the approximate 'anthropogenic portion' (see Figure 2 caption). Such a comparison has ambiguities, however, as owing to large estimates for preindustrial biomass burning [44], values relative to preindustrial can be lower than values estimated with conventional thresholds in the case of $PM_{2.5}$.

Although global values are only modestly sensitive to this methodological choice, metropolitan area deaths can be very sensitive to the choice of whether a threshold is used, and the relative magnitude of results in the two cases varies markedly across regions (Table 1/S1 versus Table S2). Cities with high current pollution levels tend to experience greater benefits from emissions reductions when a threshold is used as their pollution can drop below the threshold in the future and eliminate all impacts, whereas cities with low pollution levels tend to see greater benefits without a threshold as those results account for incremental improvements at lower exposures. Hence premature deaths in many developing country metropolitan areas decrease when the threshold is removed (e.g. totals in Delhi decrease by 18%), but metropolitan area values in many developed countries increase, sometimes greatly (e.g. totals in New York nearly triple).

Note also that the exposure-response analysis found suggestive evidence for a counterfactual for ozone-health impacts of 35 ppb below which health impacts are defined to be zero, and also reported a higher RR based on all the ozone exposures above that level (RR 1.17; 95% CI 1.11-1.22) for respiratory-related deaths [29]. Using this higher ozone threshold, 2010 all-cause premature deaths attributable to ozone decrease to 0.6±0.2 million as the exclusion of locations with $O_3<35$ ppb has a larger impact than the increased risk value.

We point out that although we have used a global model and hence presumably provide

less accurate information at the metropolitan scale than regional or local models might achieve, the mean absolute ozone bias in our model across both US and Chinese urban sites is 14%, which is substantially smaller than the uncertainties associated with the best case exposure-response function (26%) or those related to assumptions about the exposure-response relationship (e.g. the metropolitan area differences discussed above). Nonetheless, for detailed planning purposes in metropolitan areas both higher resolution atmospheric modeling and more detailed modeling of local energy and economy options would be appropriate.

As noted in the tables, uncertainties in metropolitan areas are relatively larger than those for global totals as they include uncertainties in modeling local pollutant concentrations based on mean absolute biases. For global totals, we include the mean bias in modeled $PM_{2.5}$ of 7% along with the exposure-response uncertainty (though the latter is much larger). For ozone, the bias adjustment uses all available data, so by definition the mean bias is zero, hence it is unclear what bias one would use. The mean absolute bias is 14%, but some places are overestimated whereas others are underestimated and so how model biases might affect the global total is not clear but should be less than this value and thus small compared to the exposure-response uncertainty. Overall, both exposure biases appear to be much smaller than the exposure-response uncertainties, as in prior studies (e.g. [18]).

*5. Implications of the Experimental Design regarding Feasibility and Assessment of Health Impacts*

Although we discussed economic implications of the air quality changes modeled here, this study is neither a cost/benefit analysis nor a cost-optimization exercise, but is instead intended to be complementary to IAM cost-optimization analyses by addressing a benefit that is not valued in the type of IAM that produces scenarios such as the RCPs. In scenario generation exercises, the framework is often that a goal is decided, e.g. as when the Parties to the UNFCCC set a temperature (and hence implicit radiative forcing) goal, and then IAMs are used to find the least cost path to reach that target based only on mitigation costs. In such a case, deployment of negative emissions may be projected to be less expensive than eliminating many of the most expensive fossil fuel uses (the residual in the IAM scenarios), but that is based on evaluating mitigation costs alone and not evaluating benefits, in part because by design the climate impact of alternative pathways that lead to the same climate outcome have the same climate benefits and non-climate impacts are generally not considered. Given the large air quality impacts of these choices, however, our study demonstrates that the wider societal impacts may be markedly different, and hence merit consideration alongside mitigation costs in decision-making about policy options.

It is also worth noting that while maximum phase out rates of fossil fuel usage in the IAMs are in part based on historical evidence for the maximum achievable rate of technological change, in fact real–world developments can outpace those projected in expert models. For example, a recent study showed that the actual rate of increase in installed solar electricity generation capacity outpaced each of the last four projections of the International Energy Agency despite those projections being increased with each successive revision [45]. Hence the transition away from fossil fuels might in fact be faster than envisioned in IAMs. In addition, IAMs tend to have limited representation of some land-management options (e.g. biochar or peatlands) and some demand-side mitigation options (e.g. changes in diet or food wastage, urban planning) [46]. Hence the

low carbon scenario of the RCP2.6 is but an illustrative example. Greater reductions in fossil fuel usage were not produced in the IAM generating RCP2.6 as they were assumed to be more expensive than BECCS. However, either more rapid declines in the cost of renewables or in energy demand could substantially alter such estimates. Hence the economic feasibility, which would depend upon both costs and benefits in real-world choices (though not in IAM cost-effective frameworks that do not include benefits), of the scenarios examined here is difficult to determine. A full assessment of 'feasibility' is beyond the scope of this study and would require simulation with an IAM along with a necessarily subjective evaluation of the various aspects of feasibility including technical, political, economic and societal feasibility.

Our rates and magnitude of emissions reductions vary across pollutant, but are very large for several pollutants and in particular $SO_2$ and $CO_2$ (Figure S4). We note that as $SO_2$ is only one precursor to $PM_{2.5}$, and ozone is also an important contributor to human health impacts, emissions of $SO_2$ are not necessarily a good indicator of overall health impacts of air pollution. In our scenarios in fact, $SO_2$ emissions would be a relatively poor indicator of health impacts associated with ambient air pollution, which follow carbon monoxide (or even nitrogen oxides) more closely, especially when removing population growth (Figure S5). This is likely because CO is itself an ozone precursor and is also often co-emitted with carbonaceous aerosol precursors (likewise $NO_x$ is a precursor of both ozone and aerosol). Hence utilizing $SO_2$ emissions as an indicator of air quality in future scenarios [13, 14] may not be advisable since ozone becomes the dominant driver of premature deaths by 2030 (Figure 2).

This study examines the health impacts of changes in outdoor air quality only. We note also that the accelerated reductions in residential sector emissions would bring additional health benefits related to indoor air quality beyond those analyzed here (though the RCP2.6 scenario assumed that people would move up the 'energy ladder' with projected growth in per capita incomes, leading to the rapid elimination of residential use of solid biofuels so that additional benefits would likely be small). There would also be health benefits if part of the transition to low-carbon urban transport

takes place via increased 'active transport' (walking and biking) [47, 48], though quantification would require analysis of projected transportation types beyond the scope of the scenarios explored here. As mentioned previously, in the comparisons between 1.5 and 2 degree warming scenarios, there would also be additional health benefits associated with reduced climate change (e.g. [16]).
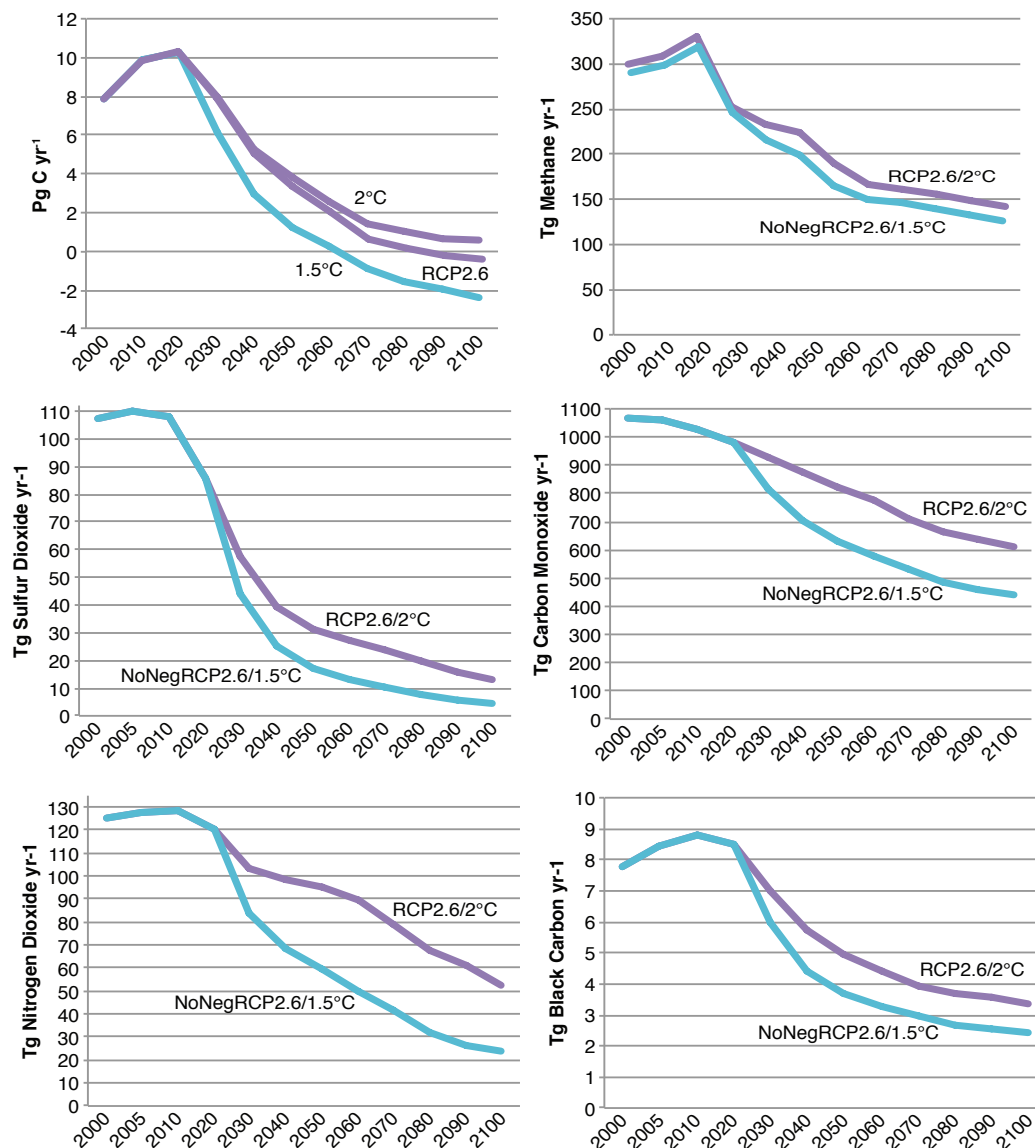


Figure S4. Emissions of major pollutants in the scenarios used here. Net $CO_2$ emissions (upper left) are shown for the 2°C, 1.5°C and RCP2.6 scenarios whereas RCP2.6/2°C and NoNegRCP2.6/1.5°C are shown for all others (as the only difference between RCP2.6 and the 2°C scenarios is for $CO_2$ based on additional carbon uptake via land management).
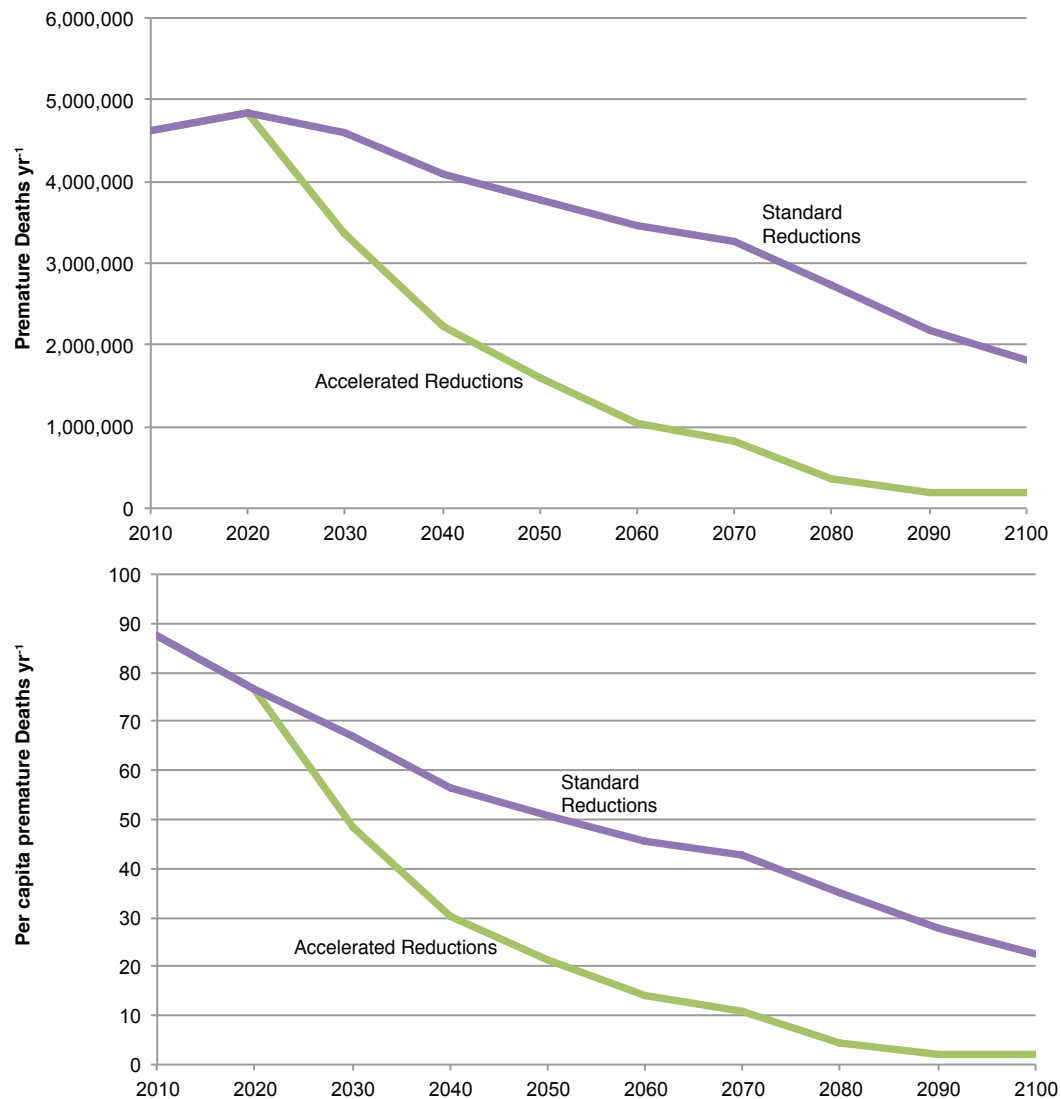
Figure S5. Total global annual premature deaths (all-cause) due to both PM$_{2.5}$ and ozone exposure (including low exposure thresholds) under the scenarios with standard emissions of non-CO$_2$ pollutants (RCP2.6 and 2°C) and under the scenarios with accelerated CO$_2$ emissions reductions (NoNegRCP2.6 and 1.5°C) expressed as totals (top) and per 100,000 people (all population for PM$_{2.5}$, >30 years of age for ozone) (bottom).

*6. Radiative Forcing over Time due to Accelerated Emissions Cuts*

We show timeseries of radiative forcing calculated with the GISS-E2 model for aerosols and ozone and with offline radiative forcing calculations following standard IPCC methodology for methane and $CO_2$ (Figure S6). Note that aerosol forcing is positive owing to reductions in cooling aerosols (sulfate, nitrate and organic carbon) that outweigh reductions in warming components (black carbon). From 2070 onwards, the net non-$CO_2$ forcing is almost exactly equal to the aerosol indirect forcing as the positive aerosol direct forcing along with positive methane forcing are cancelled out by negative ozone forcing.
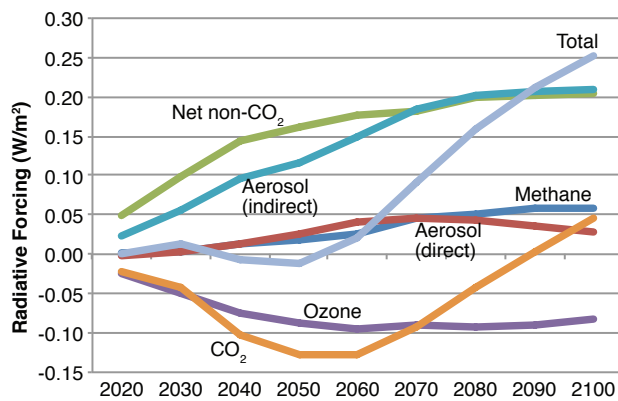


Figure S6. Radiative forcing relative to 2010 for the indicated components in the NoNegRCP2.6 relative to the RCP2.6 scenario.

**Supplementary Tables**

Table S1. As Table 1 but for metropolitan areas with greater than 1.5 million population for which there are between 350,000 and 4,000 avoided premature deaths due to accelerated emissions reductions. Values from calculations including low exposure thresholds.

| Metropolitan Area | Avoided premature deaths |
|---|---|
| Shuyang | 350,000 |
| Jinan | 340,000 |
| Yokohama | 330,000 |
| Bhopal | 330,000 |
| Moscow | 320,000 |
| Zibo | 300,000 |
| Nanjing | 300,000 |
| Mexico City | 290,000 |
| Tianjin | 290,000 |
| Surabaya | 280,000 |
| Bangkok | 260,000 |
| Accra | 250,000 |
| Seoul | 250,000 |
| Kano | 250,000 |
| Nanchong | 230,000 |
| Chengdu | 230,000 |
| Changsha | 220,000 |
| Hefei | 210,000 |
| Xiangtan | 210,000 |
| Chongqing | 200,000 |
| Sao Paulo | 200,000 |
| Wenzhou | 190,000 |
| Addis Ababa | 180,000 |
| Shenyeng | 180,000 |
| Xian | 170,000 |
| Osaka | 170,000 |
| Luoyang | 170,000 |
| Abidjan | 170,000 |
| Sanaa | 170,000 |
| Qingdao | 160,000 |
| Kyoto | 160,000 |
| Baghdad | 150,000 |
| Taipei | 130,000 |
| Los Angeles | 130,000 |
| Zhangzhou | 130,000 |
| Shijianzhuang | 130,000 |
| Xiamen | 130,000 |
| Puebla | 130,000 |
| Luzhou | 130,000 |
| Tashkent | 120,000 |
| Tangshan | 120,000 |
| New York | 120,000 |
| Tehran | 120,000 |
| Nanchang | 120,000 |
| Luanda | 110,000 |
| Taichung | 110,000 |
| Nagoya | 110,000 |
| Douala | 110,000 |
| Kabul | 93,000 |
| Fuzhou | 93,000 |
| Tel Aviv-Yafo | 93,000 |
| Pyongyang | 89,000 |
| Singapore | 75,000 |
| Guiyang | 73,000 |
| Harbin | 71,000 |
| Changchun | 71,000 |
| Wanxian | 68,000 |
| Benoni | 67,000 |
| Johannesburg | 67,000 |
| Hechi | 65,000 |
| Taiyuan | 60,000 |
| Rangoon | 59,000 |
| Baku | 59,000 |
| Daegu | 55,000 |
| London | 53,000 |
| Istanbul | 53,000 |
| Dalian | 49,000 |

| | | | | |
|---|---|---|---|---|
| Fukuoka | 48,000 | Stuttgart | 14,000 |
| Kaohsiung | 47,000 | Isfahan | 13,000 |
| Busan | 47,000 | Aleppo | 13,000 |
| Rio de Janeiro | 43,000 | Cali | 13,000 |
| Haikou | 42,000 | Sapporo | 12,000 |
| Alexandria | 41,000 | Izmir | 12,000 |
| Kunming | 41,000 | Lisbon | 12,000 |
| Bucharest | 40,000 | Sendai | 12,000 |
| Medan | 40,000 | Ankara | 11,000 |
| San Francisco | 37,000 | Frankfurt | 11,000 |
| Lanzhou | 36,000 | Toronto | 11,000 |
| Paris | 35,000 | Mashhad | 10,000 |
| Jilin | 34,000 | Kiev | 9,000 |
| Algiers | 34,000 | Miami | 9,000 |
| Beirut | 32,000 | Detroit | 8,000 |
| Damascus | 29,000 | Dakar | 8,000 |
| Campinas | 28,000 | Seattle | 8,000 |
| Hiroshima | 26,000 | Budapest | 8,000 |
| Katowice | 25,000 | Denver | 8,000 |
| Santiago | 25,000 | Nairobi | 7,000 |
| San Diego | 24,000 | Durban | 7,000 |
| Washington D.C. | 23,000 | Dar es Salaam | 7,000 |
| Palembang | 23,000 | Havana | 6,000 |
| Casablanca | 23,000 | Lima | 6,000 |
| Rabat | 21,000 | Atlanta | 6,000 |
| Philadelphia | 20,000 | Hamburg | 6,000 |
| Naples | 19,000 | Warsaw | 6,000 |
| Athens | 19,000 | St. Petersburg | 5,000 |
| Buenos Aires | 18,000 | Phoenix | 5,000 |
| Tunis | 16,000 | Vienna | 4,000 |
| Birmingham | 16,000 | Pittsburgh | 4,000 |
| Barcelona | 16,000 | Berlin | 4,000 |
| Madrid | 15,000 | Montreal | 4,000 |
| Rome | 15,000 | Jeddah | 4,000 |
| Chicago | 15,000 | George Town | 4,000 |
| Urumqi | 14,000 | Khartoum | 4,000 |
| Milan | 14,000 | | |
| Boston | 14,000 | | |

Table S2. As Table 1 but providing values from calculations without low exposure thresholds for metropolitan areas with at least 40,000 avoided premature deaths.

| Metropolitan Area | Avoided premature deaths | | |
|---|---|---|---|
| Kolkata | 3,600,000 | Xuzhou | 460,000 |
| Delhi | 3,300,000 | Suzhou | 460,000 |
| Dhaka | 3,200,000 | Jaipur | 450,000 |
| Patna | 2,700,000 | Bangalore | 440,000 |
| Lahore | 2,200,000 | Ho Chi Minh City | 440,000 |
| Mumbai | 1,800,000 | Kinshasa | 440,000 |
| Faisalabad | 1,700,000 | Beijing | 440,000 |
| Lucknow | 1,600,000 | Indore | 420,000 |
| Agra | 1,500,000 | Taian | 410,000 |
| Ibadan | 1,400,000 | Hangzhou | 410,000 |
| Dongguan | 1,400,000 | Sao Paulo | 400,000 |
| Jakarta | 1,400,000 | Chengdu | 390,000 |
| Kanpur | 1,300,000 | Tokyo | 380,000 |
| Guangzhou | 1,200,000 | Surabaya | 380,000 |
| Lagos | 1,100,000 | Shuyang | 370,000 |
| Bandung | 1,000,000 | Mexico City | 360,000 |
| Shenzhen | 990,000 | Nanjing | 360,000 |
| Cairo | 800,000 | Jinan | 350,000 |
| Pune | 790,000 | Yokohama | 340,000 |
| Ahmedabad | 780,000 | Chongqing | 340,000 |
| Shanghai | 750,000 | New York | 340,000 |
| Ludhiana | 750,000 | Bangkok | 330,000 |
| Vadodara | 740,000 | Changsha | 330,000 |
| Hong Kong | 740,000 | Nanchong | 320,000 |
| Manila | 710,000 | Xiangtan | 320,000 |
| Hyderabad | 660,000 | Addis Ababa | 320,000 |
| Kano | 650,000 | Zibo | 320,000 |
| Hanoi | 640,000 | Bhopal | 320,000 |
| Rawalpindi | 640,000 | Tianjin | 310,000 |
| Chittagong | 620,000 | Los Angeles | 300,000 |
| Karachi | 620,000 | Baghdad | 290,000 |
| Saidu | 550,000 | Hefei | 260,000 |
| Zhengzhou | 540,000 | Seoul | 250,000 |
| Nagpur | 530,000 | Wenzhou | 250,000 |
| Chennai | 520,000 | Xian | 250,000 |
| Moscow | 510,000 | Luoyang | 230,000 |
| Wuhan | 480,000 | Sanaa | 220,000 |
| Surat | 480,000 | Luzhou | 220,000 |
| | | Shenyeng | 220,000 |
| | | London | 210,000 |
| | | Zhangzhou | 210,000 |

| | | | |
|---|---|---|---|
| Accra | 200,000 | Luanda | 88,000 |
| Xiamen | 200,000 | Haikou | 88,000 |
| Nanchang | 200,000 | Antananarivo | 88,000 |
| Shijianzhuang | 190,000 | Douala | 87,000 |
| Osaka | 190,000 | Kiev | 87,000 |
| Qingdao | 180,000 | Alexandria | 86,000 |
| Taipei | 170,000 | Harbin | 86,000 |
| Rangoon | 170,000 | Dakar | 84,000 |
| Abidjan | 170,000 | Kaohsiung | 82,000 |
| Tehran | 170,000 | Boston | 82,000 |
| Fuzhou | 170,000 | San Diego | 77,000 |
| Kyoto | 170,000 | Dalian | 68,000 |
| Puebla | 160,000 | Katowice | 67,000 |
| Dar es Salaam | 160,000 | Toronto | 66,000 |
| Rio de Janeiro | 160,000 | Baku | 65,000 |
| Kabul | 150,000 | Bucharest | 65,000 |
| Tangshan | 150,000 | Milan | 65,000 |
| Benoni | 150,000 | Detroit | 64,000 |
| Johannesburg | 150,000 | Daegu | 64,000 |
| Taichung | 150,000 | Algiers | 61,000 |
| Guiyang | 150,000 | Santiago | 60,000 |
| Nairobi | 150,000 | Lanzhou | 60,000 |
| Buenos Aires | 150,000 | Fukuoka | 59,000 |
| Istanbul | 140,000 | Port-au-Prince | 58,000 |
| Khartoum | 140,000 | Dallas | 55,000 |
| Pyongyang | 140,000 | Houston | 55,000 |
| Omdurman | 140,000 | Beirut | 53,000 |
| Wanxian | 140,000 | Stuttgart | 53,000 |
| Hechi | 140,000 | Busan | 53,000 |
| Tel Aviv-Yafo | 130,000 | Atlanta | 53,000 |
| Tashkent | 130,000 | Frankfurt | 52,000 |
| Campinas | 120,000 | Bogota | 51,000 |
| Medan | 120,000 | Jilin | 51,000 |
| Paris | 120,000 | Madrid | 50,000 |
| San Francisco | 120,000 | Damascus | 49,000 |
| Nagoya | 110,000 | Miami | 48,000 |
| Chicago | 110,000 | Casablanca | 48,000 |
| Singapore | 100,000 | Durban | 46,000 |
| Birmingham | 100,000 | Budapest | 45,000 |
| Washington D.C. | 100,000 | Rabat | 43,000 |
| Taiyuan | 100,000 | Lima | 41,000 |
| Kunming | 100,000 | Barcelona | 41,000 |
| Changchun | 95,000 | Naples | 41,000 |
| Philadelphia | 95,000 | | |

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